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A Network Representation of Households by Health Exclusion, Poverty, and Unemployment

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Abstract

Social exclusion, emphasized in the European Social Agenda, presents an interesting case study on the discussion of universal vs. means-tested social policies. To understand the conditions under which universal policies may have an advantage over means-tested policies, we propose a method of network representation in which partitions are detected by background characteristics of the households. Using non-relational household level data from three countries, we map the association between exclusion from health care, unemployment and poverty. Our results show that households are less likely to form homogeneous partitioning by poverty and health care exclusion profiles, compared to the partitioning formed by poverty and unemployment characteristics. The results suggest that in cases where identifying beneficiaries is difficult, illustrated by heterogeneous partitioning, universal coverage offers an advantage over means-tested social policies.

Keywords: Exclusion; poverty; unemployment; network clustering; network representation

1. Introduction

Whether social policy should be designed by the principles of universal coverage or by means-tested programs has been subject to considerable debate both in developed and developing countries. In developing countries, means-tested policies have been actively promoted with the expectation that focusing only on the poor will entail efficient use of limited resources. While the proposal may have its merits, the efficiency aspects require careful deliberation when beneficiaries are not easily identifiable or the program area is marred with structural constraints, such as lack of service provision.

Social exclusion, emphasized especially in the European Social Agenda, presents an interesting case study for the discussions on universal vs. means-tested social policies. Following the 2000 Lisbon Agenda, the European Union (EU) highlighted alleviating social exclusion as a policy objective in member and candidate countries. To understand the extent and the depth of social exclusion, the EU proposes using social statistics, summarized by Laeken indicators (Marlier & Atkinson, 2010). Composed of three overarching portfolios, Laeken indicators on the

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one hand push for convergence of social policies across member and candidate countries; on the other hand allow for flexibility reflecting country specific conditions. A careful examination of the indicators illustrates how poverty, unemployment and social exclusion have been conceptualized as overlapping policy areas. Out of 13 of the primary indicators (European Comission, 2010), eight indicators are about measuring poverty, of the remaining five, three indicators measure unemployment.

Although both social exclusion and the efficiency of universal and means-tested programs have been examined widely in two strands of literature (Devicienti & Poggi, 2010; Fan, 2010; Sharp, 2009; Whelan & Maître, 2010), little attention has been paid to which type of policy may have a better success at integrating the socially excluded into the society. In particular, the design and implementation of socially inclusive policies require information on the processes of inclusion as well as the identification of the vulnerable. We suggest social network analysis using non-relational household-level data as a potential tool to identify when a policy design may rely on means-tested policies and when universal coverage offers an efficient way of promoting social inclusion.

In this study, our focus is on health exclusion – by which we mean the involuntary exclusion of individuals and groups from accessing to health care services available for the other members and groups in a society. We use social network analysis drawing on the homogeneity of household-level partitioning and investigate when a universal health coverage policy promotes an inclusive society in comparison to a means-tested health program. We control our results by analyzing labor market exclusion, which we define as the inability of individuals to find a job. Our results on Bosnia and Herzegovina, Macedonia and Romania are encouraging on the benefits of social network analysis as a tool in formulating inclusive health and labor market policies. Contingent on the prevalence of informal sector, active labor market programs targeting the unemployed individuals offer an efficient way to ensure re-entry to the labor market. On the other hand, inclusion into the health-care system may need a policy design independent of poverty reduction strategies as network representations suggest that universal coverage in health care may support social inclusion better than the means-tested programs.

In the remaining sections, we discuss first the literature on social exclusion. The following section describes the methodology on the construction of the networks using non-relational data and calculation of the global network properties in detail, followed by the explanations of the data. The penultimate section presents the comparative results supported with the sample statistics from the data. The final section evaluates the results with respect to the discussions on efficiency of universal and means-tested policies.

2. Social Exclusion: Definitions and Measurement

While definitions on social exclusion are abound (Beall & Piron, 2005; Hickey & Du Toit, 2007; Silver & Miller, 2003), the common denominator refers to the conditions under which individuals and subpopulations, confronted with multi-faceted barriers, are unable to access and/or afford the resources and opportunities available to other members of the society. In studies conducted for and within the EU and candidate countries, the dimensions of social exclusion are expressed by Laeken indicators, which is a portfolio of indicators on educational attainment, social relations, labor market attachment, housing and income poverty (Marlier, Atkinson, Cantillon, & Nolan, 2007).

In the empirical literature, a frequently employed statistical technique is cross-tabulation, although other methods, such as binary regressions, composite indices are explored (Avramov, 2002; Jones, Lucas, Wixey, & Aldridge, 2005). Despite the insights that each method offers, a conclusive public policy agenda has so far proved to be elusive. For instance, the empirical literature often combines income poverty with social exclusion (Gacitúa-Marió & Wodon, 2001). Several studies conceptualize monetary poverty as the lead factor of social exclusion, while in others poverty lags the conditions leading to social exclusion (Adaman & Ardic, 2008; Adato, Carter, & May, 2006). Furthermore, evidence has shown not all poor households are socially excluded, nor all socially excluded belong to poor households (Adato, et al., 2006). Position in social classes, such as caste, ethnicity results with social exclusion above and beyond monetary poverty (Beall, 2002; Chijere-Chirwa, 2002; Geiser, 2005). Nevertheless, the discovery of who might be excluded differs from the concerns on how the excluded might be integrated into the society. While the latter emphasizes the processes of inclusion, the former shifts focus on defining the marginalized and the vulnerable in the society. Hence, a careful assessment of the beneficiaries is vital and the processes should be evaluated since structural constraints, such as lack of health facilities, will hamper the coverage of the program. Social network analysis by investigating the exposure to health and labor market exclusion across the households is an attractive alternative with which the gap between identification and integration processes of the excluded can be filled.

3. Methodology

Detecting substructures within a network is proposed by Girvan & Newman, who argued, without a priori information, understanding the structure of the network becomes possible by studying tightly connected groups (Girvan & Newman, 2002). In particular, partitioning a network into clusters within which connections are dense, but between which are weak exposes the components of a network (Newman & Girvan, 2004). For instance, a partial ordering network using non-relational country level economic development data compares the clustering of countries with the ranking of each country in the Human Development Index (Hidalgo, 2010). On the other hand, because nodes may belong to several components, Ahn et. al suggest that links reveal overlapping modules within a network (Ahn, Bagrow, & Lehmann, 2010). Following previous studies (Newman, 2004), we propose network partitioning as a potential tool to compare universal and means-tested programs. To the best of our knowledge, ours is the first study to evaluate health exclusion with network partitioning and use the results to contribute to the discussions on the efficiency of means-tested social policies.

In our model, households are considered as "nodes" having three background characteristics: expenditure level, persons who are denied access to health services and unemployed persons in the household. Each of the characteristics was expressed with a score changing from 0 to 1. The households are then placed in a Cartesian coordinate where the variables are either health exclusion vs. expenditure or unemployment vs. expenditure. The households that are placed in this coordinate system are considered as nodes. Similarities between these nodes are represented with a distance metric. As such, the metric measures the distance between two households and the distance is smaller with increased similarity between the households in terms of attributes. For instance, the distance from Household A to itself is 0, by the virtue of perfect similarity to itself. For any two distinct households, the distance increases as similarities by background characteristics decrease, with the upper limit being 1.4, indicating no commonalities between the two households. This limit is the maximum possible distance between the two points placed in a Cartesian coordinate system with positions varying between 0 and 1. Once the distance matrix from each household to all other households is calculated, households within a threshold distance from each other are included in the network representation. By constructing a network with household characteristics, we exploit the multi-dimensional scaling approach proposed (Huang, Tzeng, & Ong, 2005). Using income quintiles as markers, we then identify the subsets of clusters with dense node-node connections, but for which between connections are less dense. While placement on income distribution and expenditure levels both point at household welfare, the latter captures consumption-smoothing decisions, such as saving or borrowing, thus diverges from the former.

Building a network on non-relational data presents an attractive alternative to the measurement practices employed in social exclusion literature. The clustering of households which may or may not interact but are associated by welfare and exclusion highlights the possibility that even the non-poor households may be exposed to exclusion and reveals the extent to which poverty and social exclusion are associated. Figure 1 depicts how a network depicting partitioning is constructed by the level of expenditure and exposure to exclusion from health services as two background characteristics of households. The placement of households is marked within the income distribution to detect clusters.

The methodology we follow to construct networks by health care exclusion/expenditure levels and proportion of the unemployed/levels of expenditure is characterized by global measures, such as average degree ($<k>$), average clustering coefficient ($<C>$), diameter (D) and density (d) (Barabási & Oltvai, 2004; Knoke & Yang, 2008; Newman, 2010; Wasserman & Faust, 1994). Consider a network constituting N nodes, i.e. households that are associated to each other by the profiles of their background characteristics, and l edges, i.e. defined by the similarities of profiles, degree (k) is the number of associated neighbors that one household has.

The average degree ($<k>$) for a network is defined as:

$$< k > = \frac{l}{N} \tag{1}$$

Clustering coefficient for a node (C_i) is the fraction of the number of existing connections denoting similarities among the neighbors of a particular household, l_i, to the maximum allowable connections among them. C_i ranges from 0 to 1, where 0 indicates that the neighbors of a particular household are not connected. This measure provides information on how the neighbors are connected by virtue of their similarities (Barabási & Oltvai, 2004; Newman, 2010). The average clustering coefficient (<*C*>) for a network is calculated as:

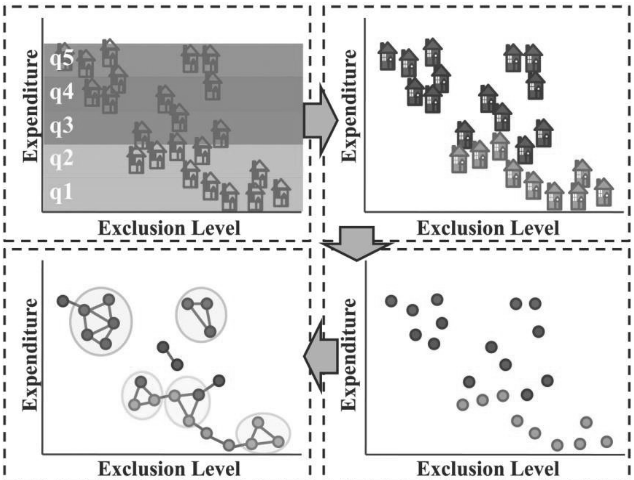


Figure 1. Computational framework of the study. Clustering households by expenditure levels and health care exclusion

$$< C > = \frac{1}{N} \sum_{i=1}^{N} \frac{2 l_i}{k_i (k_i - 1)} \tag{2}$$

Diameter (*D*) is a global property that shows the maximum distance between any two households in the network (Barabási & Oltvai, 2004; Newman, 2010; Zhu, Gerstein, & Synder, 2007).

$$D = \max \left\{ d_{ij} \middle| i, j \in N \right\} \tag{3}$$

where $d_{i,j}$ is the shortest distance between the households i and j.

Finally, the density of the network, which measures the ratio of existing associated neighbors to the total number of possible associations between the households is calculated.

$$d = \frac{2m}{n(n-1)} \tag{4}$$

where *m* is the existing connections in the network, *n* is the number of households present in the network. The application of density definition to a local community is known as the modularity, indicating the cohesiveness of a community (Spirin & Mirny, 2003).

Our primary aim is to show how analyzing the sub-components of a network contributes to the discussions on universal vs. means-tested social policies, with which households are connected as clusters by their background characteristics. We have to remind that detecting network partitioning which maps exclusion does not tell us whether the level of exclusion faced by the communities is high or low. Consider a simple scenario where households similar by expenditure level and their experience of health care exclusion are connected with a distance metric. If the analysis by these characteristics detects heterogeneous partitioning, then the results suggest that denied access to health care may have a pervasive nature across all affluence levels and support consideration of a universal coverage for health care. On the other hand, in cases where the components show dense connections by household affluence levels and exposure to health care exclusion, then a policy removing barriers for the subpopulations may have an efficiency advantage.

4. Data Source

We use the Roma Vulnerability Survey, conducted by UNDP Bratislava Regional Center in 2004, to analyze the network representation by poverty, health exclusion and unemployment. After discarding the missing observations, we had 7659 households living in the following nine countries with number of households provided in parenthesis: Albania (899), Bulgaria (935), Bosnia and Herzegovina (1171), Croatia (593), Macedonia (724), Serbia (1055), Montenegro (444), Romania (1146), and Kosovo (702). These countries share similar institutional legacy, yet the transition period governing the political and economic structures led to divergent trajectories in the last two decades. Among these countries, our selection criteria were two pronged; two countries with similar number of sampled households and two countries with similar level of income. The first criterion is to control network properties, while the second is to control the association between per capita income and the state of the health care provision in the country. The background characteristics of the households derived from the questionnaire are:

a. Adult equivalized household expenditure level (in Euro),
b. Exclusion from health services: weighted aggregation of (i) persons in the households who did not consult a doctor even though suffered an illness, (ii) people who are denied health service lacking proper documentation and (iii) people who stayed separate from other patients at the hospital, and
c. Unemployment: percent unemployed adults in each household.

While measurement of exclusion from health services was relatively straightforward, identifying precise questions on exclusion from labor market has been difficult. As a result, among survey question, the only available indicator, "proportion of unemployed adults in the household", is selected to measure labor market exclusion. We acknowledge that unemployment may result from a myriad of causes: in addition to low levels of education, temporary illness, discrimination or business cycle in the economy may drive people into unemployment. Nonetheless, in what follows, in addition to constructing networks to detect clusters, we will briefly discuss the means and averages of these three background characteristics illustrating how countries with similar averages may in fact present divergent public policy options.

5. Results

To determine whether the networks represent the sampled households, we calculated the percent coverage of the networks, which is the fraction of the number of nodes included in the networks to the number of households present in the datasets (Table 1). The networks are visualized by Cytoscape software (Shannon, et al., 2003) and organized by force directed layout, based on "force-directed" paradigm. The purpose of this layout is to position the nodes in such a way that crossing edges are minimized (Fruchterman & Reingold, 1991).We use the household's position in income distribution as a visual marker, where green color represents the lowest 20% of income distribution and blue marks the top quintile, in detecting the community structure. Once households are connected by their background characteristics and are differentiated by their placement in income distribution, the resulting network representation helps us to observe the extent to which households in the same quintiles appear in the same clusters by the level of their exposure to health care and labor market exclusion.

Table 1. Households included in network representation and their representativeness

	Bosnia and Herzegovina	**Macedonia**	**Romania**
Number of Households	1171	724	1146
Health vs Expenditure Network	947	483	1051
(% Coverage)	*(80.87%)*	*(66.71%)*	*(91.71%)*
Labor vs Expenditure Network	1043	506	1081
(% Coverage)	*(89.07%)*	*(69.89%)*	*(94.33%)*

5.1. Country 1: Bosnia and Herzegovina

Poverty and Unemployment: We start our analysis by discussing the patterns of clustering among households by poverty and proportion of the unemployed in households. These two characteristics will be closely associated at all quintile levels, undoubtedly, as unemployment is a significant constraint on household expenditure capacity (Figure 2A). The mapping shows us a persistent and close association, as expected, between poverty and percent unemployed adults in the households: households at lowest quintile are more alike, closer to each other by these characteristics, just as households at top quintiles are connected to each other. Yet, the visualization also hints at some households being different than the other households even in the same expenditure quintile, as shown by minor clusters around the grand cluster.

Overall, however, the visualization illustrates how poor households form homogeneous partitioning separate from better-off households, and thus suggests policies targeting the unemployed may identify the beneficiaries from poor households.

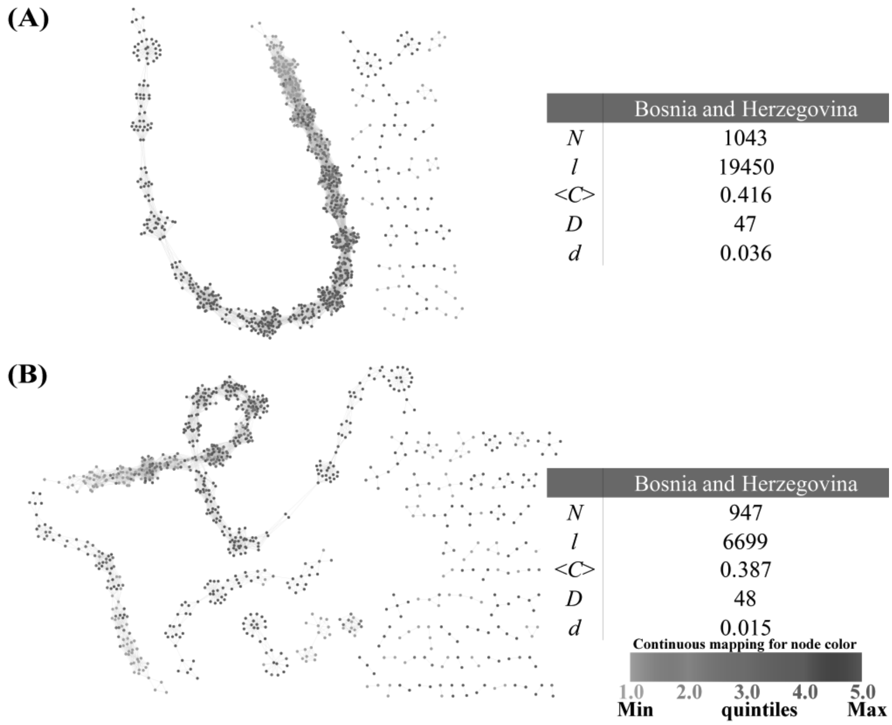
Poverty and Exclusion from Health Services: If mapping households shows a robust pattern between expenditure levels and unemployment across households, what can we expect for the pattern between poverty and exclusion from health services in Bosnia and Herzegovina? The network representation visualizing households by their similarities is depicted in Figure 2B.

There are two striking observations with respect to the network partitioning by poverty and health exclusion in Bosnia and Herzegovina. First, a significant number of poor households are disconnected, via minor clusters, from other poor households by their health care exclusion profiles and appear as a cluster by themselves, suggesting a third factor may be at play. Second, within the grand cluster, the continuity is not as robust as it was the case for poverty and unemployment, some mid-quintile households are similar in health care exclusion profiles to poor households, other mid-quintile households are connected to the better off households. The network visualization of poverty and health care exclusion profiles therefore hints at dispersed partitioning by these two background characteristics. The partitioning suggests that in Bosnia and Herzegovina identifying people who are excluded from health care services may need strategies independent of the strategies which identify the poor.

5.2. Country 2: Macedonia

Poverty and Unemployment: Our second case study, Macedonia, presents a different pattern between poverty and share of unemployed adults in the households (Figure 3A). First of all, households in the same quintile are dispersed and connected to the households in other quintiles. For instance, some of the second quintile households appear in the same cluster with the higher quintile households whereas other mid-quintile households are connected to poor households. Why might such a modular structure for poverty and unemployment happen in Macedonia? One possibility is informal sector; while there may be officially unemployed persons in households, working in the informal sector may augment household expenditures. That partitioning of clusters by household welfare is not easily detected for poverty and unemployment profiles of households lends some support to consider a universal employment generating policy, creating formal sector jobs for all, rather than active labor market policies targeting the unemployed.

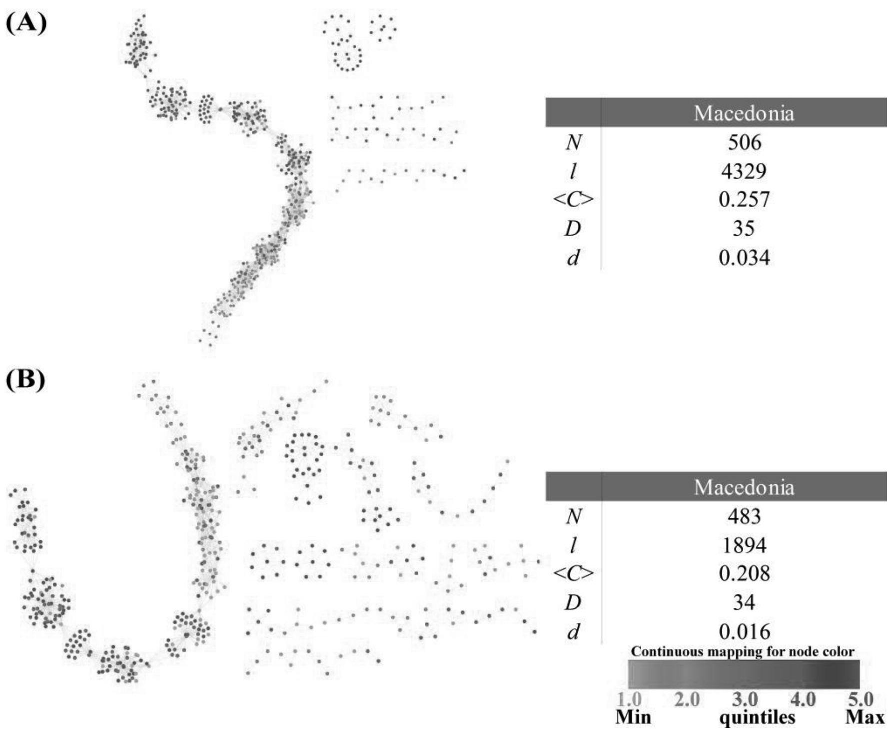
Poverty and Exclusion from Health Services: Here, the network partitioning of households by exclusion from health services and poverty presents a complex pattern, not only compared to poverty – unemployment network representation across households in the country but also poverty – health exclusion connections observed in Bosnia and Herzegovina. Exclusion from health services is experienced at all affluence levels: notice how in each sub-community, households from varying affluence levels appear in the same clusters together; poor households form communities with better-off households (Figure 3B). The difficulty in detecting sub-communities reveals that, independent of household welfare, exposure to health care exclusion is prevalent, thus suggests discovering the structural barriers in the sector impairing service provision.



	Bosnia and Herzegovina
N	1043
l	19450
$<C>$	0.416
D	47
d	0.036

	Bosnia and Herzegovina
N	947
l	6699
$<C>$	0.387
D	48
d	0.015

Figure 2. Networks constructed for Bosnia and Herzegovina (A) labor exclusion and expenditure level (B) health exclusion and expenditure level. The nodes are colored according to the income quintile of the household. Tables on the right represent the global characteristics of the networks.



	Macedonia
N	506
l	4329
$<C>$	0.257
D	35
d	0.034

	Macedonia
N	483
l	1894
$<C>$	0.208
D	34
d	0.016

Figure 3. Networks constructed for Macedonia (A) labor exclusion and expenditure level (B) health exclusion and expenditure level. The nodes are colored according to the quintile of the household. Tables on the right represent the global characteristics of the networks.

5.3. Country 3: Romania

Poverty and Unemployment: Our last case study is Romania, and we begin again with a visual mapping of the similarities between households by poverty and unemployment. In comparison to other cases, in Romania poor households are more frequent, depicted with the prevalence of bottom quintile households, denoted with green (Figure 4A).

The visual analysis of clusters reveals many of these households are very similar to each other by their poverty and unemployment profiles. The low end of the grand cluster is indicative of this pattern, with households from lowest quintile forming a cluster. On the other hand, as affluence levels increase, households are less likely to be connected to similar households. Compared to visual mapping of partitioning by poverty and unemployment in Macedonia, poor households in Romania are more likely to appear in homogeneous partitioning, separated from well-off households.

Poverty and Exclusion from Health Services: The patterns of clustering between poverty and exclusion from health services is more concentrated, with lower level of household expenditures forming a sub-community and the continuity suggests that clusters formed by household affluence levels and exclusion from health services are closely connected. The minor communities are also indicative that some of the poor households are more identifiable by their experience in health care exclusion (Figure 4B).

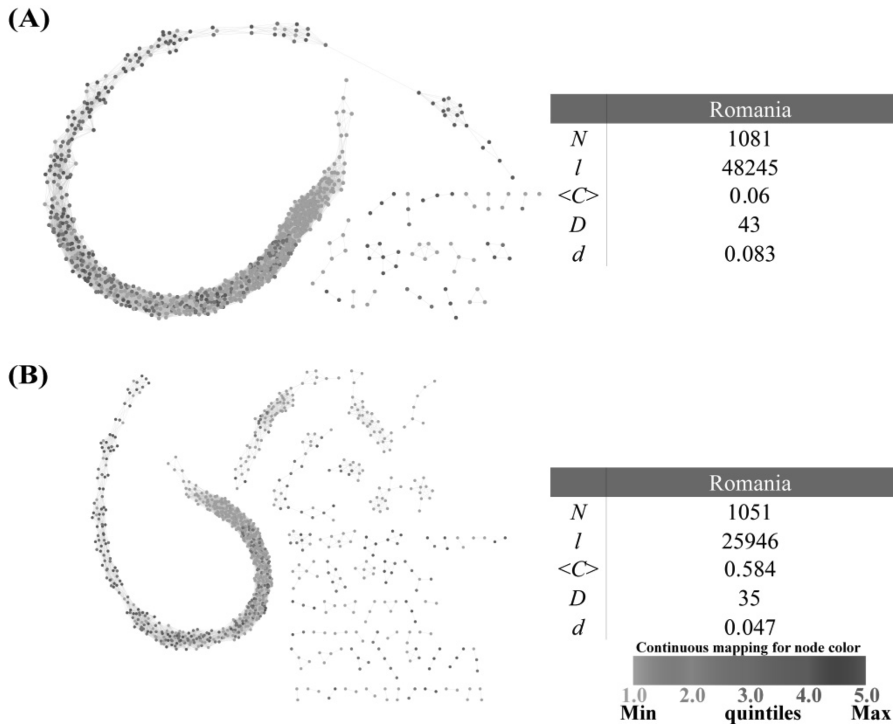


Figure 4. Networks constructed for Romania (A) labor exclusion and expenditure level (B) health exclusion and expenditure level. The nodes are colored according to the quintile of the household. Tables on the right represent the global characteristics of the networks.

6. Summary Sample Statistics

In this section, we present the statistics pertaining to the sample and highlight the differences across countries. By average household expenditures, Bosnia and Herzegovina has the highest household expenditure level, 251 Euro, followed by Macedonia, 214 Euro, and Romania, 120 Euro. Average number of unemployed persons is highest in Macedonia, 1.6 persons, lower in Romania and Bosnia and Herzegovina, approximately 1 person per household. The sample statistics for Bosnia and Herzegovina shows, on the average, at least one person reported not visiting a doctor despite an illness in the month previous to the survey. Relatively fewer persons reported exclusion from medical services due to lack of proper documentation and average number of persons reported to have stayed apart from other patients in the hospital is 0.13, with average household size as 3.7. In Macedonia, the averages for exclusion from health services indicate that people are more likely to be denied health services because of lacking proper documentation, where the average size of a household is 4.3 persons. Romania has not only lower average number of unemployed adults in households, but also fewer individuals who experienced exclusion from health care services compared to other countries.

Table 2. Sample statistics

	Bosnia and Herzegovina Mean *(Std. Dev)*	**Macedonia Mean** *(Std. Dev)*	**Romania Mean** *(Std. Dev)*
Number of Households	1171	724	1146
Household Expenditures (Euro)	251.347 *(183.255)*	214.400 *(137.511)*	120.881 *(81.091)*
Avg. No reporting Health Exclusion (Doctor)	1.025 *(1.626)*	0.533 *(1.160)*	0.790 *(1.680)*
Avg. No reporting Health Exclusion (Medical)	0.466 *(1.425)*	0.698 *(1.569)*	0.210 *(0.950)*
Avg. No reporting Health Exclusion (Hospital)	0.132 *(0.495)*	0.235 *(0.762)*	0.059 *(0.446)*
Avg. No of Unemployed in a Household	1.101 *(1.337)*	1.564 *(1.488)*	0.925 *(1.467)*
Household Size	3.763 *(2.080)*	4.302 *(2.046)*	3.821 *(2.338)*

With these sample statistics in the background, what does network representation offer as additional evidence? Let us shortly summarize the results revealed by this approach: in Romania and Bosnia and Herzegovina, network representation revealed homogeneous partitioning by poverty and unemployment profiles. Considering unemployment is associated with affluence levels, the observed homogeneity in clusters is confirmatory, and suggests active labor market policies may identify beneficiaries by poverty profiles. In Macedonia, however, partitioning by poverty and unemployment profiles indicates the potential benefits of employment-creating macroeconomic policies as an anti-poverty program alternative.

Considering exclusion from health services, the analysis depicts that network substructures by poverty and health exclusion are heterogeneous in all three countries, compared to the clustering by poverty and unemployment. Consider Macedonia, here the clustering is not dense, suggesting households placed at varying affluence levels may all experience exclusion from health care services. Furthermore, substantial number of minor clusters in Bosnia and Herzegovina suggests that, even within the same affluence levels, not all households experience health care exclusion.

Detecting homogeneous partitioning within a network reveals first and foremost, in two countries with similar average expenditure levels, households in one country may form clusters in different patterns than the ones observed in the other country. Second, the partitioning by poverty and unemployment is easier to detect than the clusters formed by poverty and health care exclusion characteristics. In the former, households are more likely to be connected to households sharing similar background characteristics. In the latter case, health care exclusion and poverty may lead to heterogeneous clusters and this holds true for all country case studies. Note how even though the sample averages show Romania as the poorest country, exclusion from health care is not as widespread at varying affluence levels as observed in Macedonia. A correlation analysis between these background characteristics, even by using income quintiles as strata, would fail to capture the differentiation between universal and means-tested policy proposals in relation to identification of beneficiaries and removing barriers in program areas.

7. Conclusion

Frequently the literature on social exclusion concentrated on the characteristics of individuals who are excluded or at risk of being excluded. While an evaluation of the potential beneficiaries is essential, identification of the vulnerable helps little to design social policies which emphasize the processes of inclusion. In this paper, we propose network representation of non-relational household data and highlight information value of the observing clusters of households with respect to monetary poverty and exposure to health exclusion. By doing so, our aim is to show social network analysis has the potential to inform the policy makers and help in the design of socially inclusive policies by filling the gap between identifying the excluded and designing inclusive processes.

Detecting substructures within a network as suggested (Girvan & Newman, 2002) adds value to the discussions on designing social policy by the principles of universal coverage or with means-tested policies. We use exclusion from health care, poverty and unemployment as background characteristics and assess the extent to which homogeneous partitioning can be detected by connecting households by their similar attributes. Our analysis shows that in two of the three countries investigated, households with similar poverty and unemployment profiles are closely associated, suggesting means-tested policies for employment creation, such as active labor market policies, may use resources efficiently. The analysis detecting sub-communities by health care exclusion and poverty suggests that universal policies in health care provision are likely to be more effective compared to means-tested programs, as heterogeneous partitioning shows that correct identification of beneficiaries may be hampered. This conclusion applies in particular to Macedonia, where denied access to health care is prevalent at all affluence levels.

Our approach in employing network analysis can be improved with further calibrations. By increasing the number of background characteristics of households, it is possible to observe clusters at detailed levels, as recently suggested (Ahn, et al., 2010). An alternative is to include spatial distribution, and observe how geospatial distribution plays a role in cluster formation. All caveats notwithstanding, a network representation aiming to detect partitioning espouses how heterogeneous formations in which beneficiaries may belong to various socio-economic strata may undermine the efficiency presumptions of means-tested social policies.

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